The Changing Economics of Knowledge Production
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Big Picture on Big Data
Big Picture on Big Data

• Goals: measure data and knowledge production

• Why data?
  ○ An endogenous source of productivity gains
  ○ Likely
    — Innovation policy relevant
    — Fiscal policy relevant
• Measuring data ($D_{it}$) and knowledge production ($f_{it}$)

$$Y_{it} = f_{it}(\{K_{it}^{j}\}, \{L_{it}^{j}\}, \{M_{it}^{j}\}, D_{it}, \ldots)$$
AV’s Magic Trick

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- Without observations on

  - $Y_{it}$ or revenues
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  ○ $D_{it}$ or data prices
AV’s Magic Trick

- Measuring data ($D_{it}$) and knowledge production ($f_{it}$)

\[ = f_{it}(\{L^j_{it}\}) \]

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  - $D_{it}$ or data prices
JP Morgan

Analysts

Data Manager (DM)
oops.. no desks

JP Morgan

Analysts

Data Manager (DM)
Analysts

- Two technologies in firm $i$:

$$Y^{OT}_{it} = A^{OT}_{t} D^{\gamma}_{it} (L^{OT}_{it})^{1-\gamma}$$

$$Y^{AI}_{it} = A^{AI}_{t} D^{\alpha}_{it} (L^{AI}_{it})^{1-\alpha}$$

- Data manager’s labor produces $D_{it}$

- Note: No other inputs or differences in TFPs
Analysts

- Two technologies in firm $i$:

\[ Y_{it}^{OT} = A_{t}^{OT} D_{it}^{\gamma} (L_{it}^{OT})^{1-\gamma} \]

\[ Y_{it}^{AI} = A_{t}^{AI} D_{it}^{\alpha} (L_{it}^{AI})^{1-\alpha} \]

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- Claim: $\alpha > \gamma$ suggests AI is “transformative innovation”
Analysts

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\[ Y_{it}^{AI} = A_t^{AI} D_{it}^{\alpha} (L_{it}^{AI})^{1-\alpha} \]

- Data manager’s labor produces $D_{it}$

- Claim: $\alpha > \gamma$ suggests AI is “transformative innovation”

- What do AV do to test this?
What do AV do?

- Use Burning Glass data:
  - Skill descriptions for analysts and data managers
  - Job postings \( \Rightarrow L_{it}^j, j = OT, AI, DM \)
  - Wage across postings \( \Rightarrow w_t^j \) (same for all \( i \!\)!)

- Solve problem of financial firm
  - Allocate analysts and managers to maximize profits
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- How do AV identify \( \alpha, \gamma \)?
Cross-Sectional Information Not Useful

- Implication of theory:
  - $w^j_t = \text{marginal product of labor}_{it}$
  
  \[
  \frac{D_{it}}{L^k_{it}} = \frac{D_{jt}}{L^k_{jt}}, \quad \text{all } i, j; k = OT, AI
  \]

  ⇒ No variation in cross-section

  ⇒ **Cannot identify** both TFPs and shares

- If variation observed, need new theory
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- If variation observed, need new theory

- What about time dimension?
Need Variation Over Time

- Implication of theory:
  - Shadow price of data = marginal product of data
  - Manipulate this condition to get:
    \[
    \Delta g(D_{it}, D_{it+1}) = \frac{\alpha}{1 - \alpha} \Delta w_t^{AI} L_{it}^{AI} + \frac{\gamma}{1 - \gamma} \Delta w_t^{OT} L_{it}^{OT}
    \]

- Suppose \( D \propto \) wages for data managers
  \[\Rightarrow\] Differential AI, OT earnings growth identifies \( \alpha, \gamma \)
Idea Behind Identification

\[ \Rightarrow \alpha > \gamma \]
There are at least two problems here..
Back to XKCD

JP Morgan

Analysts

Data Manager (DM)
Significant Overlap of Skills

JP Morgan

Analysts

Data Manager (DM)

1001
10111
000111
11100

+AI
Most Analysts are Neither OT nor AI

JP Morgan

Analysts

Data Manager (DM)
• Using AV’s criteria for 2017, we found
  ○ 110+ SOC codes for OT, AI, DM
  ○ 92% of analysts are neither OT nor AI

⇒ Not obvious that distinct technologies being used
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- What can we learn from BLS aggregates?
BLS Aggregates with AV Sample Weights

- Compute BLS earnings growth with AV
  - Industries
    - Occupation weights from Burning Glass
- With and without:
  - SOC 15-1199, Computer Occupations, All Other
Punchline: $\alpha > \gamma$ possible
Punchline: Results sensitive to groupings
Punchline: AI group includes DM types
Back to Big Picture

- Good data measurement important for policy

- Need:
  - Broader scope (beyond financial services)
  - More information on production
  - Surveys like the NSF for R&D